An Empirical Comparison of Direct Product Profit and Existing Measures of SKU Productivity

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DPP (direct product profitability) has been heralded as one of the more important advances in supermarket shelf management, yet its acceptance by managers in the industry has been slow. Not only is DPP complex and expensive to calculate, but some question exists about whether decisions based on DPP are different from those based on traditional criteria such as gross margin and movement. A data base of nine dry-grocery categories is used here to compare DPP with other SKU indices. DPP is shown to lead to significantly different rankings in some categories, but not all. A Merchandising Attractiveness Index (MAI) is devised, based on a linear regression of gross margin, dollar sales, unit sales, and shelf area occupied, which yields predicted values of DPP that are virtually identical to DPP in the nine categories studied. This MAI may be a far less expensive way to implement the basic concept of DPP. It may also be more transparent to managers for basic merchandising decisions (price, space allocation, promotions).

Several trends have emerged over the last 10 years to complicate shelf management: the increase in the number of items to manage, the bewildering array of promotional offers and associated costs/benefits of forward-buying opportunities, and the increasingly complex tradeoffs between assortment breadth, depth, and continuity. In 1988, 5,694 new

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products and 10,558 new varieties of existing products were offered to supermarket retailers (Swasy 1989). These new products crowd shelves and warehouses and force retailers to review category assortments on an almost daily basis. Although some industry analysts believe that the "average supermarket, with proper space allocation, could probably increase the number of items carried by 20 percent" (Matthews 1989), this view is probably the minority opinion. The introduction of most new items is at the expense of the space allocated to existing ones and every new item accepted is a reason to review the category for candidates to drop.

In addition to add/drop decisions, managers in charge of the thousands of individual stock-keeping units (SKUs) need a method to evaluate specific items for promotion, pricing, and space allocation decisions. Indices of SKU productivity that have been used for these purposes include: movement, gross margin, space occupied, sales per SKU and, most recently, direct product profitability (DPP).

Because no single index is perfect most merchandising decisions require looking at several indices simultaneously. There are so many SKUs to be managed, however, that only a few indices may be used at any one time. Furthermore, even if retailers could practically look at all the different indices simultaneously, tradeoffs would have to be made, and rational tradeoffs necessitate a weighting scheme. How important, for example, should gross margin be as compared with movement? How should movement be measured (cases, dollars, standardized units)? Some SKUs may earn high gross margins, but excessive handling and storage costs can outweigh their net contributions to overall profit. Implicitly, DPP represents a scheme for combining all of these considerations.

DPP reflects inter-item differences in sales, margins, and costs associated with storing, transporting, shelving, and labor-intensive merchandising activities (such as pricing individual items). Although it initially received widespread acclaim, it has since received growing criticism and many who initially adopted the DPP concept have become disillusioned (Matthews 1989) with the procedures involved in its calculation and implementation. DPP may not be the sole, or necessarily even the single best, indicator to use for all merchandising decisions, but:

(1) Assuming that DPP is the better conceptual tool for making certain merchandising decisions, would using other criteria lead to different rankings of SKUs?
(2) In those instances that DPP is believed to be a truly superior conceptual and practical merchandising tool, is there an easier way to employ the DPP concept on an everyday basis than using the complicated systems now available?

This paper uses data from a large supermarket chain to address these questions. First, we show that, depending on the category in question, commonly employed merchandising indices such as movement and gross margin may or may not be good predictors of DPP. Second, we use regression analysis to develop a multi-criteria merchandising attractiveness index (MAI) that is a surprisingly accurate predictor of DPP, may be calculated with far less effort, and is managerially intuitive. This report concludes with a discussion of some of the shortcomings of the particular research approach and how these might be addressed in the future, followed by a discussion of the management implications of our findings.

SUPERMARKET SHELF-MANAGEMENT DECISIONS AND DPP

The concept of allocating variable costs to each item and calculating specific contribution to fixed costs and profit has been around for a long time.[1] With improved models and technology came a plethora of retailer and manufacturer models designed to measure DPP. IN 1985 a unified dry-grocery-goods model was released by the Food Marketing Institute and this model has since become a standard for the industry (FMI 1986). Since then, FMI has released DPP models for magazines, meats, produce, and bakery products. The FMI models have been adopted (and adapted) by many manufacturers for use in their sales presentations, to optimize package design, and to tailor delivery systems (Bishop 1987).

Calculation of DPP

Figure 1 presents a simplified view of the FMI DPP model for dry grocery products. The required input data are of two types: (1) cost components, which are the expenses incurred for specific operations such as shelving, shipping, warehousing, and pricing, and (2) product inputs, which include information about a specific SKU such as weight, volume, sales rate, delivery method, and pallet dimensions.[2]

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[1] For a discussion on managerially controllable costs see Levy and Ingene (1984).

[2] Cost components are generally constant across all products within a given type of product, but different models are needed for different classifications (e.g., dry grocery products versus frozen foods). Product inputs must be entered for each SKU. The model then combines the product inputs and the cost components to calculate direct product cost (DPC) and DPP figures. Commonly used DPP figures include DPP/unit/SKU, DPP/week/SKU and DPP/square feet/SKU. Spreadsheet programs can be used to perform the input and analysis (FMI DPP manual).

DPP and Merchandising Decisions

The study classifies merchandising decisions into three general categories: the add/drop decision, the pricing/space allocation decision, and the promotion decision. In general, the add decision is made only once for an SKU (seasonal products are obvious exceptions). Frequently, drop decisions for existing SKUs must be made when new products are added to the assortment. SKU pricing and space allocations are reviewed periodically (new planograms, new stores, and resets), and decisions on promotions are made frequently (even if the decision is to reject a promotion offered by the manufacturer).

Add/Drop

The primary application of DPP that has been reported by some is to make add/drop decisions (Touche Ross 1988). However, for new items the only DPP figures available would be projections and subject to the optimism of the manufacturers. Selecting items to drop or reduce in shelf space in order to make room for the new items is quite a different decision. Although actual sales and DPP are potentially available for these decisions, when Farris, Olver, and DeKluyver (1989) surveyed buyers on the decision criteria used to select particular SKUs to drop the survey showed that DPP was rarely used, even by those buyers with DPP systems in place. Movement, gross margin, and even "service from the supplier" dominated DPP considerations. For those buyers surveyed, it appears that DPP is relevant to drop decisions only when used to further differentiate between items with low rates of sales. If an SKU is selling well, but earning low DPP, an obvious solution is to raise prices. If sales remain stable, the increased price and margin would lead to improved DPP. Only if sales fall and DPP remains low should the item be dropped.

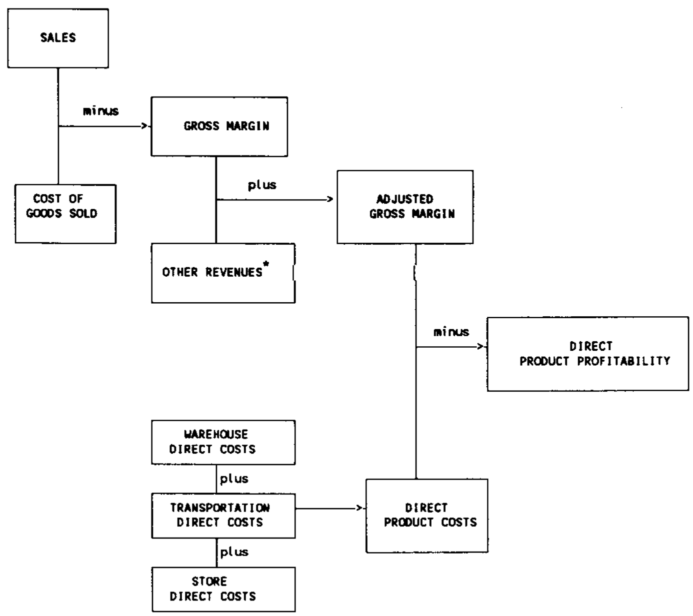
For theoretical and practical reasons movement is the primary criterion used for selecting items to drop; DPP is secondary (Jacober 1986; Weiss 1987; Merrefield 1987). Thus, if DPP is not a primary criterion for drop decisions and if only projected figures are available for add decisions, it may not be sensible to employ full-scale DPP analysis in these situations.

Pricing/Space Allocation

DPP/SKU/unit (percent of selling price or dollar amount) sold is a variable that is conceptually superior to gross margin for setting prices, especially for items that do not have significant traffic-building effects and/or affect total category sales. If direct costs are associated with handling

FIGURE 1

Direct Product Profit Computation



* Deals, allowances and other direct revenues

SKUs, then gross margin would generally overestimate the true marginal revenue from incremental sales. This outcome would lead to errors in pricing levels and structure. On the other hand, if revenues other than those reflected in its selling price are associated with sales of a given SKU (as in the case of traffic builders, for example), then either DPP or gross margin could underestimate marginal revenues. In that case, DPP, being generally less than gross margin, could make errors in pricing based on gross margin even worse. Movement and number of customers buying a particular SKU give some indication of how likely an item is to play such a traffic-building role for the retailer.

A similar problem relates to using DPP as the sole criterion for allocating shelf space. If too little space is allocated, stock outs will occur, and even if short-term category sales and profits do not suffer, long-term category sales may. Furthermore, if a customer is lost to another retailer, the loss is far greater than the lost revenues from a single category would predict. Similarly, if promotion of an item increases sales in other categories, neither gross margin nor DPP will reflect these benefits.

DPP's Prospects for the Future

The evidence on acceptance of DPP is conflicting. In a 1988 study by Touche Ross International (Touche Ross International 1988), 40 percent of the responding retailers and 60 percent of the manufacturers were using DPP; almost 100 percent were planning eventually to use it.[3] This evidence is not in agreement with surveys by Farris, Olver, and DeKluyver (1989), who reported that only 23 percent were using DPP systems. Significantly, less than one-quarter of buyers who had DPP systems were using DPP for add/drop decisions at the SKU level. This low usage level may reflect a poor understanding of DPP, the time and effort to implement DPP, and/or a feeling that the manager can achieve the same results with present systems (70 percent of the manufacturers, 85 percent of the wholesalers, and nearly all of the retailers believed that DPP was not understood by the industry (Donegan 1988). Clearly, DPP education is still needed.

It is also clear that it takes a great deal of time and expense to collect and input the data required by DPP systems. Forty product inputs and over seventy cost inputs are required for its computation. Advocates of DPP stress the additional information that DPP provides relative to alternative measurements. This argument would not be as credible if it can be shown that a weighted combination of readily accessible sources of data provide significant DPP predictions. Four commonly used measures of SKU productivity include: gross margin, dollar sales, unit sales, and square feet of shelf-space allocation. These measures are often used either individually or collectively to make listing/delisting, shelf space/pricing, and promotional decisions. If it is shown that a simple correspondence between these four variables and DPP exists, it is reasonable that retailers might use them for everyday within-category decisions and reserve the more complicated DPP for major category reviews.

DATA

A large retail supermarket chain supplied the cost components and product inputs required in the FMI-DPP model. Cost components included

[3] Many believe that manufacturers' interest in DPP stems from the fact that the model they produce tends to bias the results in their favor. Furthermore, manufacturers of high-DPP categories such as cigarettes and greeting cards encourage its use (Weiss 1987).

time and motion figures for labor productivity such as cases/hour and pallets/hour which were measured at the warehouse, transportation, and store levels. Using the industry-standard FMI model, these cost components were used to calculate DPC and DPP for individual SKUs. Cost inputs are standard across all dry-grocery categories. The SKU variability enters through the product-input section of the model where specific item information such as case pack, price, movement, and transportation method is recorded. The industry-standard FMI model was used to combine the product inputs with the cost standards to arrive at a dollar-direct, cost-per-unit amount incurred at different stages in the channel. These costs include warehouse ordering, receiving and stocking, transportation, store ordering, receiving, stocking, and selling. The total of all these direct costs represents the item's DPC—direct product costs.

Nine product categories[4] were selected to examine the relationship between DPP/week/SKU with space costs[5] and currently used profitability measurements or cost factors including gross margin dollars/week/SKU, package sales/week/SKU, dollar sales/week/SKU and square feet of space allocation. The selection of the specific dry-grocery categories was based on the availability of data.

Descriptive analysis of the categories is presented in Table 1. Six SKUs had negative gross margins and thirty-four had negative DPP with space costs.[6] Negative gross margins and DPPs may be explained by either (1) loss leader effects, (2) unaccounted allowances and/or deals,[7] (3) pricing mistakes. Across and within-category variation is readily apparent.

ANALYSIS

Univariate regressions were performed for each category to determine the strength of association between DPP and the individual measures of movement, space allocation, and gross margin. The results in Table 2 show that gross margin has the strongest relationship with DPP in all categories except peas, with an R^2 range of .08 to .99. Dollar sales and unit movement were significant in seven of nine categories. Space allocation

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[4] Categories include: canned green beans, canned corn, canned peas, canned mushrooms, jelly, peanut butter, jams/preserves, sheet fabric softener, ketchup. The categorization of items was determined by buyers/merchandisers.

[5] DPP/week/SKU with space costs is the most commonly used figure. Space costs are based on the amount of retail shelf space occupied (Boyle 1988).

[6] The nine categories included a total of 268 items.

[7] In some instances cash allowances cannot be allocated to individual items.

TABLE 1

Category Descriptive Statistics

	DPP/week/SKU				Gross Margin Dollars/week/SKU				Dollar Sales/week/SKU			
	Sum	Mean	Min.	Max.	Sum	Mean	Min.	Max.	Sum	Mean	Min.	Max.
Green beans	17.04	0.59	−0.52	4.71	52.93	1.83	0.26	11.92	252.37	8.70	0.60	60.20
Corn	14.41	0.58	−0.79	4.77	54.69	2.19	0.32	12.51	297.91	11.92	1.91	66.39
Peas	4.80	0.27	−1.91	1.49	26.34	1.46	−0.11	7.23	157.76	8.76	0.71	62.74
Mushrooms	28.33	1.67	0.46	3.10	37.22	2.19	0.66	4.10	137.63	8.10	1.48	18.03
Jelly	28.18	0.55	−0.80	3.57	43.26	0.85	−0.35	4.08	165.13	3.24	0.66	18.54
Peanut butter	53.37	1.52	−5.04	7.77	81.03	2.32	−3.96	10.72	544.60	15.56	2.44	81.49
Jams/Preserves	52.56	0.86	−0.68	5.41	71.88	1.18	−0.34	5.91	229.74	3.77	0.83	13.81
Fabric softener	36.43	2.28	0.48	6.57	49.42	3.09	0.98	7.86	211.71	13.23	5.22	33.49
Ketchup	3.20	0.20	−4.97	5.53	27.41	1.71	−0.35	8.19	227.62	14.23	1.60	62.25

	Unit Movement/week/SKU				Square Footage/SKU				Number of Category Items
	Sum	Mean	Min.	Max.	Sum	Mean	Min.	Max.	
Green beans	599.06	20.66	0.50	168.03	30.16	1.04	0.23	1.67	29
Corn	758.14	30.33	4.01	185.17	27.71	1.10	0.40	2.43	25
Peas	375.31	20.85	0.55	175.46	17.10	0.95	0.24	2.08	18
Mushrooms	162.75	9.57	0.59	35.63	7.66	0.45	0.23	0.80	17
Jelly	142.59	2.80	0.37	18.73	25.11	0.49	0.11	1.09	51
Peanut butter	299.10	8.55	1.26	67.68	22.96	0.65	0.44	1.35	35
Jams/Preserves	133.52	2.19	0.32	7.32	32.55	0.53	0.13	0.87	61
Fabric softener	105.49	6.59	1.49	16.13	13.55	0.84	0.77	0.88	16
Ketchup	193.63	12.10	1.97	63.00	26.85	1.67	0.31	3.61	16

TABLE 2

Univariate Regressions of Product Indices and Direct Product Profit[a]

	Gross Margin R^2	Dollar Sales R^2	Package Sales R^2	Square Feet of Space R^2
Green beans	.91	.80	.74	.21
Corn	.91	.83	.82	.02*
Peas	.08*	.04*	.03*	.17*
Mushrooms	.94	.72	.40	.42
Jelly	.94	.61	.45	.15
Peanut butter	.96	.58	.34	.07*
Jams/Preserves	.99	.72	.39	.00*
Fabric softener	.99	.76	.41	.10*
Ketchup	.64	.02*	.09*	.00*
All Categories	.73	.29	.07	$-.00$

[a] Adjusted R^2.

* Insignificant at the .05 level.

results show that this independent variable was the poorest predictor of an item's DPP.

Category and Pooled Regression Analysis

Although the results of the univariate regressions showed that in some cases gross margin or movement indicators have a strong predictive relationship with DPP, the results were not consistent enough across categories to justify replacing DPP with any *one* measurement. To determine whether a combination of these variables can predict SKU DPP, within-category multiple regressions were run. These results are presented in Table 3. Each of the nine categories had an adjusted R^2 greater than .98. For the peas category, moving from univariate to the multivariate regression increases R^2 from a high of .17 to .99. The average category percent error listed in the right column ranged from 1.8 to 10.7 percent.

Consistent with earlier results, gross margin was the only variable significant in all categories. To determine whether a weighted combination of the alternative measurements can be applied across categories a pooled regression was run. The results at the bottom of Table 3 demonstrate that the strength of the relationship is maintained.

TABLE 3

Multivariate Regression of Product Indices and Direct Product Profit

	Gross Margin Beta	Dollar Sales Beta	Unit Sales Beta	Square Feet Beta	Constant	R^{2} [a]	Percent Error[b]
Green beans	1.03	−.04	−.03	−.31	−.05	.99	4.7
Corn	.99	−.01*	−.03	−.37	−.03	.99	4.9
Peas	1.00	−.01*	−.04	−.35	−.04	.99	1.9
Mushrooms	1.18	−.07	−.02	−.44*	.03	.99	4.4
Jelly	1.15	−.10	.02*	−.23	−.01	.98	10.7
Peanut butter	1.00	−.01	−.05	−.50	.04	.99	2.8
Jams/Preserves	.98	−.03	−.01*	−.29	−.01	.99	4.7
Fabric softener	.99	−.01*	−.03	.05*	−.47	.99	1.8
Ketchup	1.09	−.03	−.05	−.32	−.08	.99	7.4
All Categories	1.06	−.03	−.03	−.43	.03	.99	

* Insignificant at the .05 level.

[a] Adjusted R^2.

[b] Average absolute value of the category residuals/Average absolute value of category DPP (in percent).

The weights from the multivariate regressions were used to compute predicted DPP values. This value will be referred to as a merchandising attractiveness index, or MAI (except where specifically noted the weights are from the category-specific regressions). Figure 2 illustrates for a selected category the relationships between the alternative measurements and DPP as well as the MAI and DPP. Figure 3 illustrates these relationships for all categories, based on weights from the pooled regression. The MAI relationship provides an extremely good fit—further support of a predictive inference. The plots also highlight an important point—there is a one-to-one correspondence between SKUs with negative DPP and negative MAI values.

The regression weights for individual components of the MAI are intuitively appealing. Gross margin has a weight very near 1.0 and the other weights are negative. This implies that the three independent variables other than gross margin are explaining the direct product costs part of the DPP equation (i.e., DPP = gross margin minus direct product costs). Space costs are associated with that variable; shelving, pricing, and other merchandising costs are associated with the number of units sold; and inventory investment expenses are associated with dollar sales. Of course the multicollinearity among these variables means that the coefficients are unstable and causal interpretation would be suspect. Even though multicollinearity is not as serious a problem for purposes of prediction, further tests for predictive stability were performed.

Two separate checks of the stability of the predictive power of the MAI coefficients were performed. First, a split-half test was conducted on the pooled regression results. Consistent with the approach outlined by Pedhazur (1982), one-half of the sample was randomly selected and used in a multiple regression. The coefficients were then used to compute the MAI (predicted DPP) from the second sample and a Pearson correlation was then calculated between the MAI and the actual DPP.[8] If the difference between the R^2 in the first sample and the second is small, then the regression coefficients may be applied to future predictions. The Pearson coefficient was .9936, which was significant at the .001 level ($n = 134$) and the difference in R^2 between the two samples was .007. The root mean-squared error for the holdout sample was .17 (the average absolute value of DPP in the holdout sample was 1.12; for the entire sample it was 1.08).

Second, the pooled coefficients were used on a category by category basis to produce the MAI. Direct product profit was regressed on the calculated index and the results presented in Table 4. The large R^2 suggests that regression coefficients produced from SKUs across a variety of categories can be used to predict DPP within any selected category. This is further evidence that multicollinearity is not a cause for serious concern as regards predictive ability of DPP with the components of MAI. Indeed, the high multicollinearity means that the model might be simplified with little loss in R^2.

Simplified MAI

A simplified MAI was produced with two and three variable versions of the four-variable MAI. Pooled regression analysis was performed to determine which two- and three-variable subsets provided the best fit. Results indicate that gross margin and unit movement with an R^2 of .98 outperformed all other two-variable combinations. Similarly, gross margin, unit movement, and square foot of space allocation was the best three-variable set ($R^2 = .99$). The root mean-squared error for the MAI-3 hold-out sample was .26, while that for the MAI-2 was .36. The simplified MAIs were regressed on a category by category basis and the results presented in Table 4. The predictive power is surprisingly strong for the two- and three-variable MAI equations.

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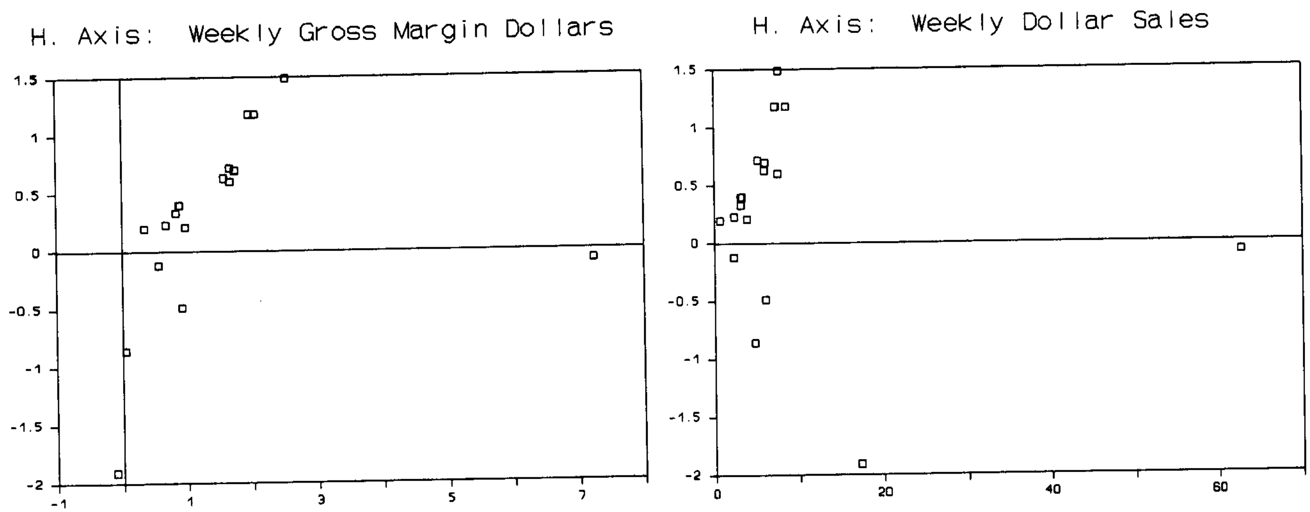
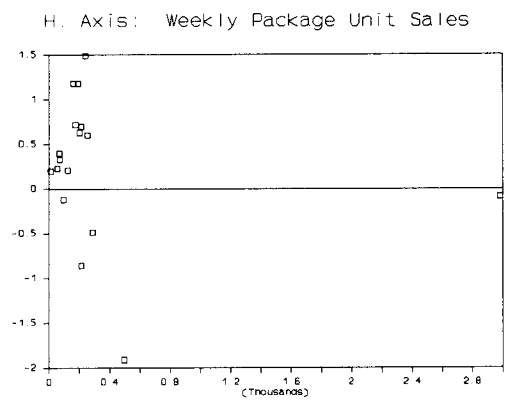
[8] Coefficients for the first random sample were: gross margin (1.02), dollar sales ($-.02$), unit movement ($-.03$), and space ($-.40$).

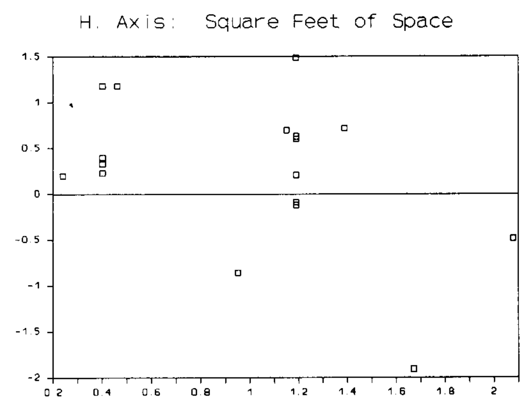
FIGURE 2

The Relationship Between DPP and Alternative Measurements, Category—Peas

(Vertical Axis—Actual DPP per week with space costs)




H. Axis: Weekly Package Unit Sales
(Thousands)


H. Axis: Square Feet of Space

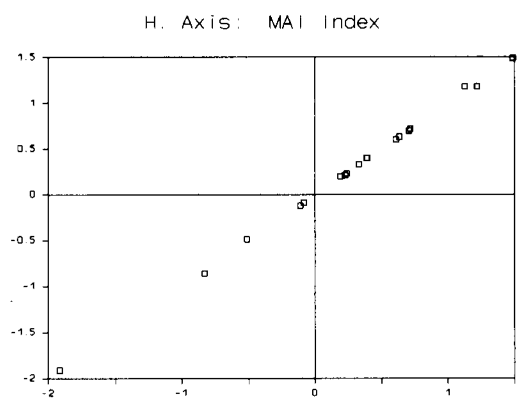
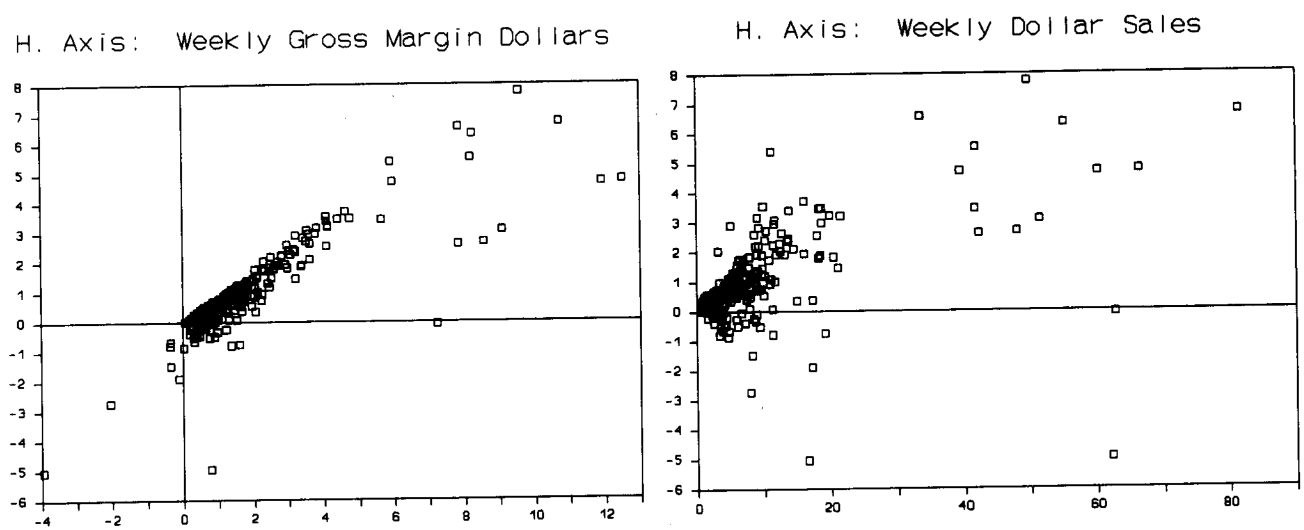

H. Axis: MAI Index

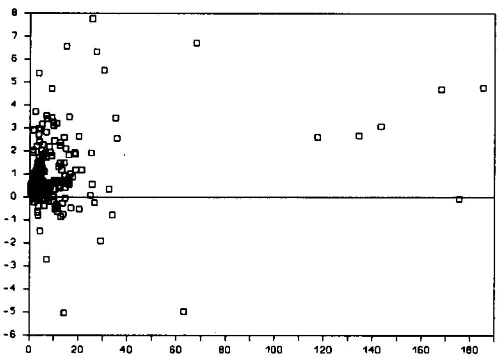
FIGURE 3

The Relationship Between DPP and Alternative Measurements, All Categories

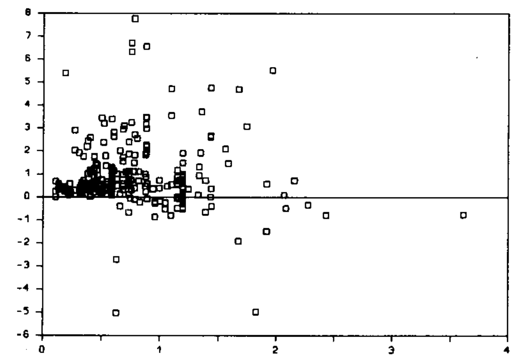
(Vertical Axis—Actual DPP per week with space costs)



H. Axis: Weekly Package Unit Sales



H. Axis: Square Feet of Space



H. Axis: MAI Index

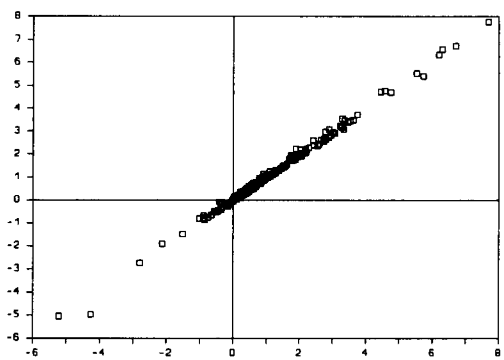


TABLE 4

Univariate Regressions Using MAI Pooled Coefficients Within Categories

Category	4-Variable MAI[a] R^2	3-Variable MAI[b] R^2	2-Variable MAI[c] R^2
Green beans	.99	.99	.98
Corn	.99	.99	.98
Peas	.99	.99	.93
Mushrooms	.98	.98	.98
Jelly	.98	.97	.96
Peanut butter	.99	.99	.99
Jams/Preserves	.99	.99	.99
Fabric softener	.99	.99	.99
Ketchup	.98	.91	.88

[a] Weekly Gross Margin, Dollars, Unit Movement and Square Footage

MAI-4 = 1.06GM − .03DOL. − .03UM − .42SF + .03

[b] Weekly Gross Margin, Unit Movement and Square Footage

MAI-3 = .96GM − .04UM − .49SF + .06

[c] Weekly Gross Margin and Unit Movement

MAI-2 = .95GM − .04UM − .28

DISCUSSION

Direct product profit is a relatively time-intensive and expensive profitability measurement that continues to confuse many members of the retail community. The major purpose of this research project was to analyze the relationships between commonly used profitability measurements and space allocation and direct product profit. The results demonstrate that the best single predictor of DPP is gross margin dollars, followed by dollar sales, package unit sales, and square feet of space allocation. More importantly, these four measurements used together in a multiple regression can account for over 98 percent of the variability in SKU DPP.

The regressions used to predict DPP incorporate data that are commonly used and understood by industry and their relationship with an SKU's profit potential is evident. Their weights can be used to calculate a merchandising attractiveness index that should be useful as a surrogate for DPP decisions that do not permit more time-intensive calculations.

An additional advantage of the MAI is the reduced number of input variables required for its calculation after the initial calibration. Seventy-five cost components and 40 product inputs are initially required for a DPP analysis and an MAI calibration. However, after the weights are computed, only four, three, or two MAI variables must be gathered and input to recalculate an item's MAI. This is significantly fewer than the 40 DPP variables required when an item first enters the system and the 17–26 variables that are periodically changed for an item currently in the system.

Limitations

The earlier discussion outlined the difficulties inherent in DPP calculations. Though the study demonstrated that for these nine specific categories the regression coefficients were consistent across product types, these results would not be expected across all categories or within a category across stores. The extremely high predictive power found in this study was not expected by the authors or DPP professionals that were consulted. Whether future studies across stores and/or other categories will confirm our results is an empirical proposition that remains to be investigated. For instance, space allocation weights should be significantly different for bulky products such as diapers or paper towels.

Future Research

Additional data is presently being gathered to conduct validation studies to measure the stability of the MAI coefficients within and across a wide variety of categories. The present study included both direct store-delivered and warehoused items as well as private labels and branded items. Further studies might examine bulky high-variable cost categories versus non-bulky categories. Due to the nature of some of these items, the same high predictive power of the MAI may not be obtained, or radically different weights may be required for equivalent predictive power. Furthermore, testing should be done on additional independent variables or variants of the existing measures (e.g., dollar sales per square foot). Finally, alternative measures of DPP such as DPP/SKU/week without space costs, DPP/unit, and DPP per unit of space allocation should be incorporated into the study. A more ambitious goal would be the construction of an MAI that might apply across stores. Unless the variables are transformed in a way that eliminates cost differences between stores (perhaps share variables could be used), there is no reason to expect the same high predictive power from common coefficients.

If further research confirms the ability of MAI to predict DPP it may save large amounts of time and expense now being undertaken to recalculate the variable on an everyday basis or to evaluate new products. Also, the components of the MAI and its relative weights are far more transparent to managers than the procedures used to calculate DPP. Thus, they may feel more comfortable implementing the concept of DPP through a simplified MAI.

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